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Impact of machine reliability data uncertainty on the design and operation of manufacturing systems

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Abstract

Decision making in the design and operation of advanced multi-stage manufacturing systems is more and more supported by digital manufacturing tools. In order to be effective in their scope, such tools have to be based on high-fidelity virtual representations of the real system. To achieve this goal, they are continuously fed with process and system data directly collected from the field. Once validated, these digital tools can be used to evaluate and generate alternative system improvement actions and optimized re-designs of the system, based on scenario analysis. Traditionally, manufacturing systems engineering methods suitable to this scope include analytical methods and simulation. While evaluating the performance of the system under a given configuration, they typically assume that machine reliability parameters (Mean Time to Failure and Mean Time to Repair) are precisely known. However, in practical situations, these parameters are either estimated from real life data or based on experts' knowledge. In both cases, they are subject to estimate uncertainty. This paper investigates the risks and the potential performance losses due to design and operation decisions derived by neglecting machine reliability uncertainty in the digital manufacturing tools. The proposed method paves the way to the on-line adoption of digital models for manufacturing system continuous improvements.

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Keywords: Manufacturing Systems, Uncertainty, Robust Design;

1. Introduction

Digital manufacturing tools are becoming more and more important in the design and operation of manufacturing systems due to their increasing complexity and the need of continuously meeting evolving and challenging production targets. In order to be effective in their scope, such tools have to be based on high-fidelity virtual representations of the real system. To achieve this goal, they are continuously fed with process and system data directly collected from the field. However, the impact of the accuracy of these data on the results of the performance evaluation and the consequent system design process is hardly ever taken into account, thus mining the robustness of the adopted design/re-design solutions. An accurate and robust performance analysis of unreliable manufacturing systems is therefore an important step to achieve design target performances with an adequate level of confidence. Modeling incomplete knowledge and parameters' uncertainty as perfectly accurate information leads to several fundamental risks for manufacturers. Firstly, there is an inherent risk that system configurations fail to meet the target performance, in real settings. Secondly, system over-sizing and resource capacity waste can be observed. This directly translates into additional costs. Therefore, effective decisions on the design and reconfiguration of manufacturing systems strongly rely on the ability to carry out a sound performance analysis and system design process, incorporating parameters' uncertainty within the digital model of the system.

This uncertainty may be caused by internal or external sources; internal uncertainty is related to imprecise characterization of the events that affect the technical efficiency of the resources in the system, i.e. breakdowns and failures; external uncertainty is related to the difficulty in prediction of the system design requirements, mainly due to the market volatility and turbulence. In this paper, we will focus on the first source of uncertainty, i.e. internal uncertainty.

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From a practical point of view, a systematic approach towards internal uncertainty is an essential step to support both the "green field" design and the re-configuration phases. During the "green field" design phase, the technical efficiencies of the resources/machines that shall compose the manufacturing system are considered as nominal values, provided by the equipment/sensor producers. However, when installed and integrated in the system, these resources typically prove to perform differently from what expected, due to the specific operational conditions and control system settings. Therefore, in order to capture this deviation in the "green field" design phase and to generate a robust system configuration, uncertainty should be associated to the resource efficiency estimates. On the contrary, in the system operational phase, the technical efficiency of the machines can be estimated by using historical data, i.e. the machines' operational records, typically stored in the company production monitoring system database. In this case, estimates are subjected to uncertainty due to the specific sampling plan adopted.

Performance analysis with an explicit consideration of associated uncertainty is of paramount importance for generating system configurations/reconfigurations that are robust to input parameter estimation uncertainty. Such analysis allows understanding how the uncertainty associated to each input parameter impacts the overall uncertainty in the output performance measure, and to refine the level of confidence of the input parameters accordingly (i.e. by increasing the data acquisition effort on the most relevant parameters, as shown in Fig.1).

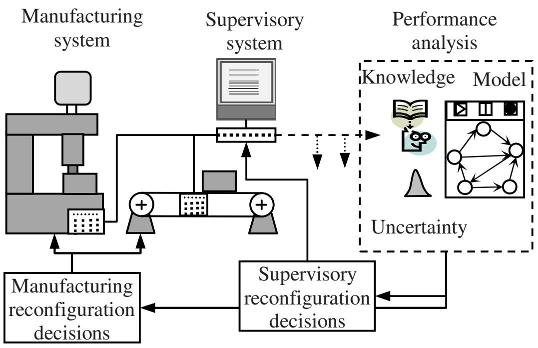

Fig. 1. Integrated data acquisition and performance analysis.

In spite of the industrial relevance of this problem, state-of-the-art Manufacturing System Engineering approaches, including both simulation and analytical methods [1], [2], never considered this issue. The advantages of performance evaluation based on real operational data which reflects actual behavior of the system are discussed in [3] and [4]. Particular emphasis on the application of data collection for the analysis of machine and component level reliability parameters are highlighted in [5] and [6]. Moreover the growing strategic importance and wide spread implementation of supervisory and data acquisition systems (SCADA) to collect data at manufacturing systems level and current trends are discussed in [7], [8].

In this paper, a new approach for the performance analysis of manufacturing systems when machine failure and repair parameters are known with uncertainty is proposed. It is based on the combined use of Bayesian estimation and analytical techniques for analyzing manufacturing lines composed of unreliable machines and capacitated buffers. The two major research questions that this paper aims at answering can be formulated as follows: "What is the error in the estimation of the system throughput observed if only the expected values of the estimated input parameters are considered, i.e. uncertainty is neglected?" and "What system design decisions can be significantly affected by this error?". The results show that internal uncertainty modifies the performance evaluation results and can significantly affect the related system design decisions, thus paving the way to the development of a new manufacturing system engineering theory for the robust design of manufacturing systems under uncertainty.

2. System Description

Although the proposed approach is general and can be in principle applied to any manufacturing system layout for which approximate analytical methods are available, in this paper we will focus on serial manufacturing lines.

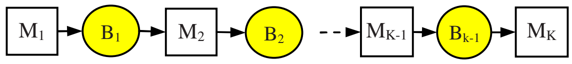

Fig. 2. Representation of serial manufacturing lines.

The modeled serial production line is composed of K unreliable machines separated by K-1 limited capacity buffers, as represented in Fig 2. The machines (squares) perform operations on parts flowing in the system. Buffers (circles) have the role of decoupling the machines in the system. They can be either inventory storages or automated material handling systems that transport semi-finished materials between machines. The i^{th} machine and buffer are denoted with M_i and B_i (with i=1,…, K-1,K) respectively: B_i has capacity equal to N_i and it contains only pieces already worked by M_i. A generic M_i is blocked if the downstream B_i is full and is starved if the upstream dedicated buffer B_{i-1} is empty.

2.1. Modeling Assumptions

The detailed list of modelling assumptions follows:

- A discrete material flow model is considered.

- Machine processing times are deterministic and equal for all the machines in the system. The time unit is scaled to the processing time.
- Machine M_i can fail in F_i independent failure modes.
- Times to Failure (TTF_{ij}) and Times to Repair (TTR_{ij}) are geometrically distributed.
- Failures are Operational Dependent Failures (ODF), i.e. the machine can fail only if operational (not starved or blocked).
- Machine M_i fails in failure mode $j=1,..,F_i$ with probability $p_{i,j}$ in a time unit. We assume the value of $p_{i,j}$ is not precisely known, therefore $p_{i,j}$ follows a probability density function (pdf) $f^p_{i,j}$. In case of availability of historical data on the machine behavior, $p_{i,j}$ can be estimated from s samples of $TTF_{i,j}$, for example through Bayesian inference (next section).
- A failed machine, M_i *is* repaired in a time unit with probability $r_{i,j}$. We assume the value of $r_{i,j}$ is not precisely known, therefore $r_{i,j}$ follows a pdf $f^r_{i,j}$. If sample data are available, the distribution of $r_{i,j}$ can be estimated as shown for $p_{i,j}$.

The performance measures of interest are the system throughput *TH*, i.e. the average number of parts produced by the system in a time unit, and the average level of each buffer in the system n_i, $i=1,..,K-1$.

2.2. Parameter Inference

Although the inference schema is presented for the generic failure probability p, it is applied to all the uncertain parameters in the system. A Bayesian framework allows modeling the state of knowledge about uncertain parameters with respect to the observations made in a time period and it integrates new observations as they become available. If there exists a prior $\pi(p)$, then the posterior density $\pi(p|TTF)$ after s new observations of *TTFs* will be updated by using the Bayes formula as follows:

$$\pi(p\,|\,TTF) = \frac{\pi(p)\pi(TTF\,|\,p)}{\int_P \pi(p)\pi(TTF\,|\,p)dp} \qquad (1)$$

In our analysis, we use the conjugate priors for the characterization of unknown failure and repair parameters. Since *TTFs* are geometrically distributed by assumption, then p follows a $Beta(\alpha_p, \beta_p)$ distribution.

$$\pi(p) = \frac{1}{B(\alpha,\beta)} p^{\alpha-1}(1-p)^{\beta-1} \qquad (2)$$

Where $B(\alpha,\beta)$ is the Euler integral of the first type. The likelihood after observation of a vector of *TTFs* is;

$$\pi(TTF\,|\,p) = \prod_{i=1}^{s} (1-p)^{TTF_i - 1} p = (1-p)^{\left(\sum_{i=1}^{s} TTF_i - s\right)} p^s \qquad (3)$$

Substituting (2) and (3) in (1) and after manipulations:

$$\pi(p\,|\,TTF) = Beta(\alpha + s, \beta + \sum_{i=1}^{s} TTF_i - s) \qquad (4)$$

This provides the new posterior distribution p ~ $Beta(\alpha'_p,\beta'_p)$ after a sample s of new observations of *TTFs,* where $\alpha'_p = \alpha_p + s$ and $\beta'_p = \beta'_p + (\Sigma\, TTF_i) - s$.
At any observation time, all uncertain parameters can be characterized in the same way using their conjugate prior distributions. Normally most of performance evaluation models use the mean of these observations as input, i.e. the maximum likelihood of (4).

$$\hat{p} = \arg\max\{\pi(p\,|\,TTF)\} = E[\pi(p\,|\,TTF)] = \frac{\alpha'}{\alpha' + \beta'} \qquad (5)$$

Instead the proposed method evaluates the output performance using the density function of the estimated parameter given in (4).

3. Method description

A possible approach to solve the stated problem would be to apply Monte Carlo (MC) simulation. This would consist in sampling values of $p_{i,j}$ and $r_{i,j}$ from the original *pdf*s and in applying a performance evaluation method, for example a decomposition-based approximate analytical method, to compute the output performance for any combination of the sampled parameters. By repeating this approach the output performance distribution can be approximated. In order to avoid several replicates, in this paper we focus on a similar procedure that instead of sampling uses *pdf* partitioning and discretization to determine the set of parameter settings to be evaluated by the approximate analytical method that considers precisely known input.

3.1. Partitioning and discretization

The discretization requires the definition of a sufficient number of partitions T_u for a predetermined level of accuracy, for each uncertain parameter q_u, with $u=1,\ldots,U$. For consistency, all the uncertain parameters, $p_{i,j}$ and $r_{i,j}$ for each station M_i, are mapped in a convenient order to the generic parameter q_u, $u=1,\ldots,U$. The lower and upper limit $q_{u,min}$ and $q_{u,max}$ are determined to enclose an area approximately equal to 1 under the original *pdf,* f^{qu}. The Δq_u partition width can be calculated as:

$$\Delta q_u = \frac{q_{u,\max} - q_{u,\min}}{T_u} \qquad (6)$$

If x_0 corresponds to $q_{u,\min}$ and x_{Tu} corresponds to $q_{u,\max}$ each partition bound x_{tu} is obtained as:

$$x_{t_u} = q_{u,\min} + t_u \cdot \Delta q_u \qquad t_u = 1,\ldots,T_u \tag{7}$$

Each partition weight, w_{tu}, and the centroid value of the random variable, $q_u(t_u)$, in the considered partition are then approximately computed as follows, for $t_u=1,\ldots,T_u$:

$$w_{t_u} = \frac{f^{q_u}(x_{t_u-1}) + f^{q_u}(x_{t_u})}{2} \Delta q_u \tag{8}$$

$$\hat{q}_u(t_u) = x_{t_u-1} + \frac{\Delta q_u (2 \cdot f^{q_u}(x_{t_u}) + f^{q_u}(x_{t_u-1}))}{3 \cdot (f^{q_u}(x_{t_u}) + f^{q_u}(x_{t_u-1}))} \tag{9}$$

This procedure transforms the probability density function of the uncertain parameter into an equivalent probability mass function (*pmf*). It can be repeated for all the U uncertain input parameters of the problem, for $u=1,\ldots,U$. Then a set of $(T_u)^U$ experiments with precisely known inputs are generated from the combination of all the considered values of the U random variables.

3.2. Performance evaluation with precisely known input.

For each experiment, a decomposition based approximate analytical performance evaluation method is adopted to calculate the main performance measures under precisely known input settings. Firstly, the original line is decomposed into a set of K-1 sub-systems $l(i)$, named building blocks. These are composed of two pseudo-machines, $M^u(i)$ and $M^d(i)$, and one buffer, $B(i)$. Building blocks are easy to solve because of their lower complexity compared to that of the original system. The coherence of building blocks is made possible by the definition of decomposition equations that establish proper relationships among them. According to the decomposition logic, all the interruptions of the material flow entering (leaving) the buffer $B(i)$ are modeled by the pseudo-machine $M^u(i)$ ($M^d(i)$), including starvation (blocking) events. The parameters of these pseudo-machines are iteratively updated by considering the performance of the neighboring sub-systems by decomposition equations, until convergence is met. The decomposition equations for our system assumptions are provided in [1]. Upon convergence, the performance measures of the system can be computed as follows:

$$TH = TH(i),\ n_i = n(i) \tag{10}$$

3.3. Output performance statistics.

With the objective of reconstructing the overall performance measure distribution, the following procedure is adopted (here reported only for the throughput). For each experiment featuring a specific combination of realizations $(t_1,t_2,..,t_U)$ of the U input uncertain parameters, the weight of the combination is computed as follows:

$$w(t_1, t_2, \ldots, t_U) = \prod_{u=1}^{U} w_{t_u} \tag{11}$$

By using these weights, the throughput distribution can be easily reconstructed. Moreover, interesting statistics can computed from this distribution, such as the mean and the variance of the average throughput estimate. This technique can be generally applied to different performance analysis problems involving uncertain inputs, provided that a performance evaluation method is available for precisely known inputs.

4. Numerical Results

In this section, the impact of considering uncertainty in the input parameters on the system performance evaluation and the subsequent system design decisions is investigated.

4.1. Performance Evaluation under Uncertainty

Firstly, our approach that embeds uncertainty is compared with traditional approaches that only include the expected value of input parameters to compute the output measures. The deviation between the mean throughput estimated by considering deterministic input parameters and the mean throughput estimated by the method proposed in this paper is the response of interest. A simple buffered two-machine line is considered. A set of thirty randomly generated cases have been considered where $p_{1,1}$ of the first machine and $r_{2,1}$ of the second machine are uncertain. Surprising results are found. The percentage difference of the estimated throughput is higher than 5% in 90% of the cases and a maximum deviation of 15% is observed. This practically means that with traditional approaches that neglect input parameters' uncertainty decisions are based on very poor performance estimates. This can potentially lead to poor system designs. This emphasizes the importance of analyzing manufacturing systems by including in the analysis the input parameter uncertainty for a robust performance evaluation.

4.2. Impact on System Design

Secondly, the impact of parameters' uncertainty on the optimal system design is investigated. In particular, the problem of setting inventory levels in multi-stage systems is considered. In its original formulation, the buffer allocation problem searches for the minimal total buffer space that is required to meet a desired target throughput level TH^*. However, it is solved in the literature only for precisely known input reliability parameters. While including the internal uncertainty in the analysis, the robustness of the solution becomes a critical aspect. Therefore, we formulate a new buffer allocation problem that consists in searching for the minimal total buffer capacity that is required to meet a desired throughput level, TH^*, with a specified confidence level, $(1-\gamma)$. In this formulation, γ is the accepted risk of failing while meeting the target throughput requirement. More formally, the decision variable is the vector of buffer sizes $\boldsymbol{N}^*$ defined as $\boldsymbol{N}^*=\text{MIN}(\boldsymbol{N}|\text{Prob}(TH\geq TH^*)>(1-\gamma))$. In the following, we investigate the relation between the solutions to the original and the new buffer allocation problems in systems with uncertain parameters.

A two-machine line system with data reported in Table 1 is used as test system. In this simple case, a single buffer size N has to be selected. The problem is to determine the minimum level of N^* that is required to achieve the target throughput TH^*=0.84. The accepted risk is $\gamma = 0.01$.

Table 1. Input data for the buffered two-machine line.

$E[p_1]$	$\sim p_1$	r_1	p_2	r_2
0.025	Beta(20,β)	0.21	0.0234	0.23

The effect of increasing the number of observations on the robust design is investigated. For the given problem, we increased the number of observed failure time records from 20 to 2000 and we solved the buffer design problem without considering uncertainty and including uncertainty at two levels of risk, i.e. γ=0.1 and γ=0.01. The results are reported in Fig. 3 together with the long run solution. As it can be noticed, by relying on more failure observations, the input uncertainty decreases and the safety overcapacity provided by the robust design decreases. Moreover, as more data are considered for the analysis, the three solutions get closer to the long-run solution. Generalizing this result, when fewer real system observations are considered, the robust design approach provides a system solution that have high probability of actually meeting the production rate target. However, this is paid in terms of additional capacity to be assigned to the system. On the contrary, if uncertainty is neglected, there is a high chance to fail in meeting the target performance. Instead, when more real system observations are considered, the advantages of the robust design are less evident with respect to the approach that neglects uncertainty. The practical consequence of this behavior is the following. At a given point in time, one can decide to improve the system based on the available data through a robust approach, , or he can postpone the decision, waiting for the availability of more production records that can decrease the input parameters' uncertainty, thus decreasing the system oversizing due the robustness requirements. This trade-off can be addressed by economical evaluations that are out of the scope of this paper.

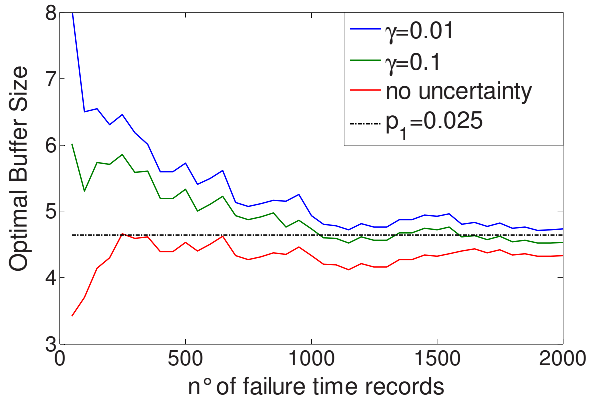

Fig. 3. Effect of increasing the n° of failure records on robust design.

4.3. Inventory Allocation in Long Lines

In this experiment the same buffer allocation problems are considered for four lines composed of 10 machines. The parameters of machines are reported in Table 2. Each machine has a failure probability that is subject to uncertainty. The target throughput is TH^* = 0.75 for each case. The risk level is fixed at γ=0.05. The optimal inventory distributions obtained by the proposed method (*Robust*) that includes uncertainty and by using the traditional method (*No Unc.*) are reported in Table 3.

Table 2. Data for 10 machine lines.

ID	A	B	C	D
$E[p_1]$	0.007	0.007	0.007	0.007
$Var[p_1]$	$6.93\ 10^{-7}$	$6.93\ 10^{-7}$	$1.39\ 10^{-6}$	$1.39\ 10^{-6}$
r_1	0.095	0.095	0.094	0.095
$E[p_2]$	0.007	0.008	0.008	0.01
$Var[p_2]$	$6.93\ 10^{-7}$	$7.9\ 10^{-7}$	$1.59\ 10^{-6}$	$1.98\ 10^{-6}$
r_2	0.095	0.094	0.095	0.09001
$E[p_3]$	0.007	0.006	0.003	0.003
$Var[p_3]$	$6.93\ 10^{-7}$	$5.93\ 10^{-7}$	$5.93\ 10^{-7}$	$5.99\ 10^{-7}$
r_3	0.095	0.093	0.045	0.09102
$E[p_4]$	0.007	0.007	0.004	0.005
$Var\ [p_4]$	$6.93\ 10^{-7}$	$6.93\ 10^{-7}$	$7.93\ 10^{-7}$	$1.00\ 10^{-6}$
r_4	0.095	0.094	0.078	0.09903
$E[p_5]$	0.007	0.005	0.006	0.001
$Var[p_5]$	$6.93\ 10^{-7}$	$4.95\ 10^{-7}$	$1.19\ 10^{-6}$	$1.96\ 10^{-7}$
r_5	0.095	0.095	0.069	0.09504
$E[p_6]$	0.007	0.006	0.007	0.009
$Var[p_6]$	$6.93\ 10^{-7}$	$5.94\ 10^{-7}$	$1.38\ 10^{-6}$	$1.77\ 10^{-6}$
r_6	0.095	0.093	0.094	0.09205
$E[p_7]$	0.007	0.009	0.008	0.009
$Var[p_7]$	$6.93\ 10^{-7}$	$8.9\ 10^{-7}$	$1.59\ 10^{-6}$	$1.77\ 10^{-6}$
r_7	0.095	0.095	0.095	0.09706
$E[p_8]$	0.007	0.008	0.003	0.003
$Var[p_8]$	$6.93\ 10^{-7}$	$7.93\ 10^{-7}$	$6.00\ 10^{-7}$	$5.98\ 10^{-7}$
r_8	0.095	0.094	0.045	0.09607
$E[p_9]$	0.007	0.007	0.004	0.008
$Var[p_9]$	$6.93\ 10^{-7}$	$6.93\ 10^{-7}$	$7.93\ 10^{-7}$	$1.59\ 10^{-6}$
r_9	0.095	0.096	0.078	0.09208
$E[p_{10}]$	0.007	0.008	0.006	0.007
$Var[p_{10}]$	$6.93\ 10^{-7}$	$7.93\ 10^{-7}$	$1.19\ 10^{-6}$	$1.38\ 10^{-6}$
r_{10}	0.095	0.095	0.069	0.09409

As it can be noticed, for all four lines the proposed method provides an inventory distribution that allows to meet the target throughput at the required risk level (Table 4). On the contrary, by adopting a traditional approach that neglects uncertainty, the average throughput is met but with a resulting confidence level that is largely below the fixed value (close to 0.5, Table 4). Also in this case, the total inventory required in the robust solution is larger.

Table 3. Results for 10 machine lines.

ID	Method	Buffer B_i									Tot
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
A	No Unc.	5	5	9	10	10	10	9	5	5	**68**
	Robust	5	6	10	11	11	11	10	6	5	**75**
B	No Unc.	5	6	8	9	10	11	10	6	5	**70**
	Robust	5	7	9	10	11	11	11	8	5	**77**
C	No Unc.	5	7	9	12	13	14	11	5	5	**81**
	Robust	5	9	11	14	16	16	14	7	5	**97**
D	No Unc.	5	5	6	7	8	10	7	5	5	**58**
	Robust	5	7	7	8	8	12	9	6	5	**67**

Table 4. Throughput statistics for the robust design (γ=0.05).

ID	A	B	C	D
E[TH]	0.7614	0.7610	0.7687	0.7662
Var[TH]	$3.97\ 10^{-5}$	$3.93\ 10^{-5}$	$1.14\ 10^{-4}$	$8.38\ 10^{-5}$
TH and risk level γ for the traditional approach				
TH	0.7500	0.7501	0.7500	0.7501
γ	0.497	0.495	0.500	0.499

5. Case Study

The D12 line producing engine blocks in SCANIA CV AB is analyzed to show how uncertainty impacts the system design decisions in a real manufacturing system context. The line is composed of 22 machines in series. In this paper, we focus on the first five machines in the line, i.e. from OP020 to OP060. Each of these five stations is affected by six failure modes (30 failures in total). The analysis is based on actual data collected from the company production monitoring system. Specifically, nine months of data concerning failure and repair occurrences were available (≈10,000,000 operation cycles). The objective of the analysis is to reconfigure the inventory for achieving an average throughput *TH* of 0.50 for this production line branch with a confidence level $(1-\gamma)$ of 0.99. The current buffer configuration is $N^{current}$ = [7, 9, 4, 4].

The analysis made by neglecting the uncertainty in the estimation of the input reliability parameters provides a new optimal configuration: N^* = [11, 10, 10, 8]. The value of E[*TH*] for this configuration is slightly greater than 0.500, but the result only provides 54% of guarantee that the target *TH* will be actually satisfied due to uncertainty. By solving the problem with the proposed approach that embeds uncertainty the optimal buffer configuration is N^* = [11, 11, 11, 8]. This results in a risk of only 0.001 that the throughput will not actually be met. If compared with the theoretical results proposed in the previous section, in this analysis the overcapacity needed to ensure the required robustness level is very limited (+2 buffer modules). This is due to the fact that the analysis grounds of a very large set of real-life data records, that reduce the input parameter uncertainty. Consequently fewer additional buffer capacities smartly placed in the line bring higher chances in terms of system robustness to uncertainty.

6. Conclusions

In this paper, the practical implications of considering uncertainty in manufacturing system design / redesign are emphasized, in contrast with the traditional trend of assuming precisely known reliability parameters. Moreover, typical system design problems, such as the problem of finding the optimal allocation of inventory to meet a desired target throughput, have been formulated and solved. For these problems it is shown that the configuration obtained by neglecting the machine reliability uncertainty can be sub-performing or even unfeasible, failing to meet the design requirements. Finally, new data collection policies for directly increasing the level of confidence of the system design and operation decisions are proposed. Future studies will aim at improving the applicability of the proposed method to a wider set of problems and system layouts.

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